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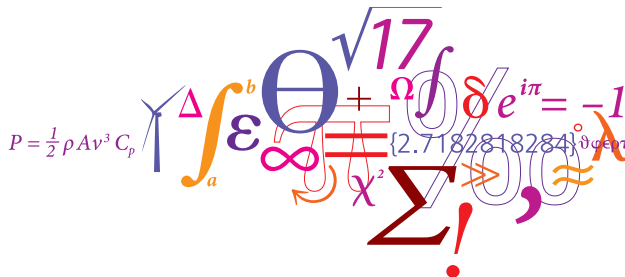
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Higher Fidelity Analysis in Wind Turbine Multi-disciplinary Design Optimization

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- Direct Optimization at Higher Fidelity
 - Medium Fidelity Analysis Tools
 - The FE Based Vortex Dynamics
 - Optimization Results
- Multi-fidelity Design Optimization
 - The AMMF Algorithm
 - Structural Design Case Study
- Closing Statements

Direct Optimization with Higher Fidelity Analysis

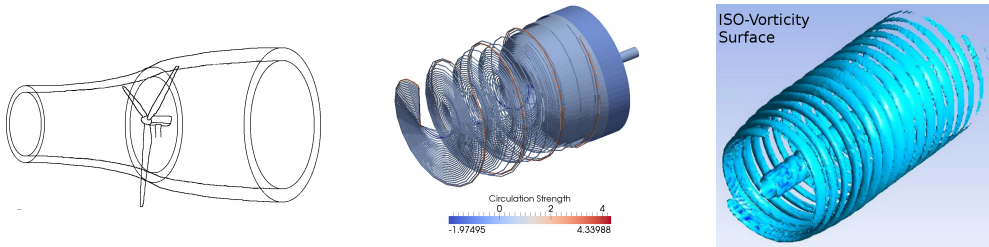


- Trends show wind turbines are getting larger
 - Higher turbines better winds
 - Improved economies of scale (e.g. offshore)
- Future growth will require advanced designs
 - Bend-twist coupling, curved blades, active load alleviation, winglets, coning, etc.
- Multidisciplinary Design Optimization (MDO)
 - Simultaneously optimize multiple disciplines (e.g. aero, structural, control, etc.)
 - Optimization based on holistic metrics (e.g. cost of electricity)
 - Wind turbine design constrained by unsteady loads (i.e. strong gusts and fatigue)

Medium Fidelity Analysis Tools

Direct Optimization with Higher Fidelity Analysis

Analysis Tools



- Conventional preliminary design tools
 - Blade Element Momentum Theory and Linear beam theory
 - Fast and efficient, but lacks the fidelity required by advanced designs
- High fidelity analysis
 - Grid-based CFD and Shell and Brick based FEM
 - Excellent fidelity, very expensive for optimization
- Need medium fidelity analysis (improved fidelity, still efficient)
 - Vortex Dynamics (VD)
 - Nonlinear beam theory (GEBT)
 - Anisotropic Cross Section Analysis (VABS)

Direct Optimization with Higher Fidelity Analysis

Aero-elastic Optimization with Conventional VD

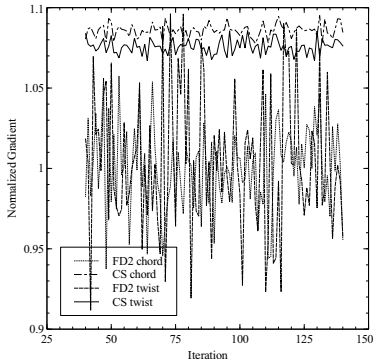


Figure from Lawton and Crawford 2015

- Aeroelastic model with Conventional VD, GEBT and VABS
- Obtained optimization results with
 - Pure aerodynamic
 - Aero-elastic with fixed wake
- Failed to obtain aeroelastic results with free wake simulations
 - Pure vortex methods are fundamentally chaotic
 - Numerical noise spoils the gradients and optimization
- **Conventional VD not suitable for aero-elastic optimization**

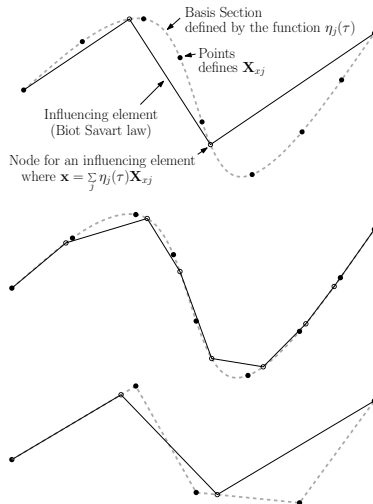
Michael K. McWilliam, Stephen Lawton, and Curran Crawford. "Towards a framework for aero-elastic multidisciplinary design optimization of horizontal axis wind turbines" In AIAA Annual Sciences Meeting, 2013

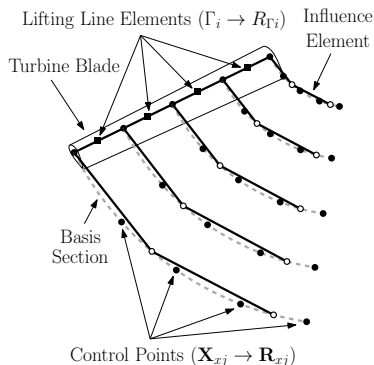
The Finite Element Based Vortex Dynamics

- Vortex position in the wake defined by interpolating splines:

$$\mathbf{x} = \sum_j \eta_j(\tau) \mathbf{X}_{xj} \quad \dot{\mathbf{x}} = \sum_j \dot{\eta}_j(\tau) \mathbf{X}_{xj}$$

- Can have an arbitrary number of influence elements and control points
 - Can add more influence elements to improve accuracy
 - Can remove control points to accelerate calculations





- Convergence defined by a residual:

$$\mathbf{r}_x \equiv \dot{\mathbf{x}} + \boldsymbol{\Omega} \times (\mathbf{x} - \mathbf{x}_0) - \mathbf{u}_\infty - \mathbf{u}_\gamma$$

- Mapped to control points through Galerkin projection:

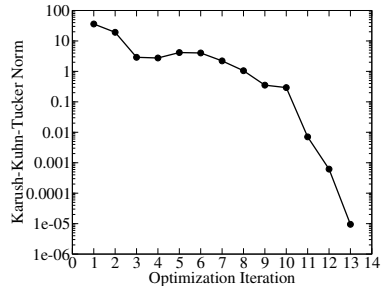
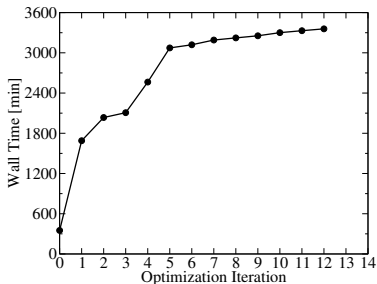
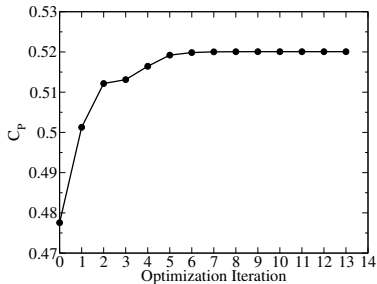
$$\mathbf{R}_{xj} = \int_{\tau_0}^{\tau_f} \zeta_j(\tau) \mathbf{r}_x(\tau) d\tau$$

- Solved with a Newton iteration
 - Adaptive relaxation required to get reliable convergence
 - **See Video for example**
- Best results with a far-wake model
 - Avoids singularities
 - Eliminates wake-truncation errors

Optimization Results

Direct Optimization with Higher Fidelity Analysis

Optimization Convergence with FEM-Based VD

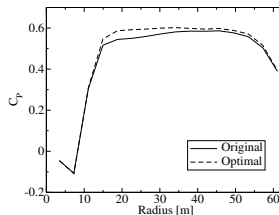
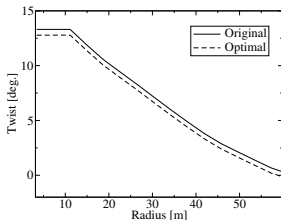


- Used analytic gradients
 - Explicit VD residual definition predicts changes in state
- Tight optimization tolerances
- Small changes avoid singularities

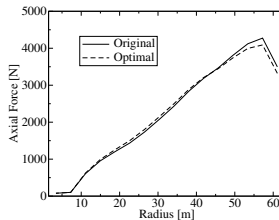
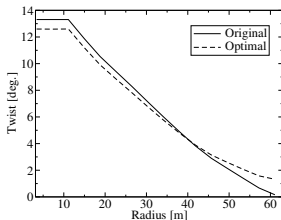
Direct Optimization with Higher Fidelity Analysis

Optimization with FEM-Based VD

Aerodynamic Only Optimization:



Aero-elastic Optimization:



- Aeroelastic optimization created more efficient designs

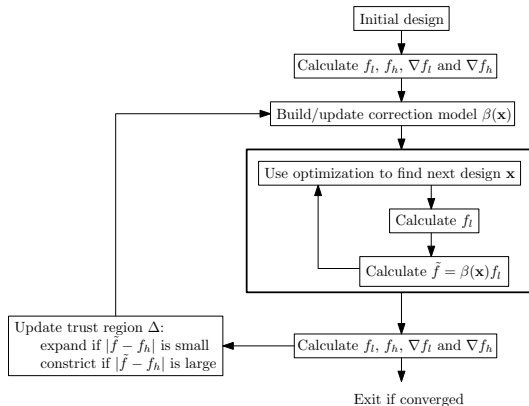
Multi-fidelity Design Optimization

- Uses both a high fidelity and low fidelity model
 - Less expensive by using fewer high fidelity results
 - Reduces surrogate error with low-fidelity results
- Fidelity could be based on:
 - Formulation (e.g. RANS vs. BEM)
 - Grid resolution (e.g. fine vs. course)
 - Type of simulation (e.g. unsteady vs. steady)
 - etc.
- Low fidelity just needs to show similar trends

The AMMF Algorithm

Multi-fidelity Design Optimization

The AMMF Algorithm



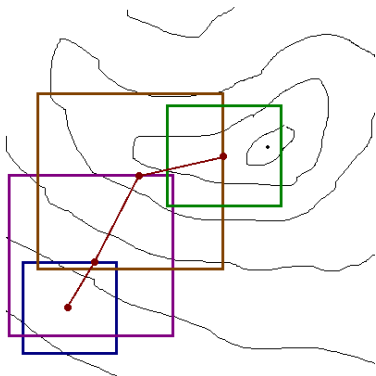
- High fidelity used for accuracy
- Low fidelity is used for speed
- Correction for first order consistency

$$\tilde{f}(x) = f_l(x) + \beta(x)$$

$$\begin{aligned}\beta(x) &= f_{h0} - f_{l0} \\ &\quad + (\nabla f_{h0} - \nabla f_{l0}) \Delta x\end{aligned}$$

- Trust-region for robustness

- The trust-region defines the region where we can “trust” our approximation
- Constrained to stay within the trust-region
- Re-centered at every major iteration
 - Only when an improved is found
- Trust region is resized
 - If the approximation gives excellent agreement then it grows
 - If the trust region gives poor agreement then it shrinks
 - If the inner optimization fails to find an improvement, it will repeat within the smaller trust region
 - Similar to the line search algorithm
 - Otherwise maintain the trust region



Multi-fidelity Design Optimization

Constraints in the AMMF Algorithm



- Constraints are corrected in the same way
- The constraints are present in the low fidelity optimization
- Constraints receive special treatment in Approximation and Model Management Framework (AMMF)
- First an estimated Lagrangian is calculated

$$\Phi = f + \tilde{\lambda}_e \cdot |\mathbf{c}| + \tilde{\lambda}_i \cdot \max(0, -\mathbf{c}_i)$$

- $\tilde{\lambda}$ are the Lagrange multipliers estimated from previous iterates.
 - $\tilde{\lambda}$ is specified for the first iteration
- New iterate only accepted when $\Phi_i < \Phi_{i-1}$
- Trust region is expanded or contracted based on M :

$$M = \frac{\Phi_{i-1} - \Phi_i}{\Phi_{i-1} - \tilde{\Phi}_i}$$

- Trust region expanded if M is close to 1
 - Trust region contracts if M is far from 1

Multi-fidelity Structural Design Optimization

Multi-fidelity Design Optimization

Summary of Low Fidelity Tools

Position	EA	Elx	Ely	GJ
0.05	0.0	2.6	-4.9	-5.4
0.15	0.5	1.1	-3.0	-0.8
0.25	-0.4	-1.8	2.1	-1.4
0.35	-0.7	-2.6	1.7	-3.1
0.45	-0.7	-3.1	1.0	-5.5
0.55	-0.9	-3.1	-0.3	-7.7
0.65	-0.8	-2.9	-1.7	-9.3
0.75	-0.6	-2.2	-2.2	-9.2
0.85	-0.6	-1.7	-3.5	-5.9
0.95	-0.1	-1.2	-2.0	-2.0

Table: Percent Error with BECAS

- Low fidelity cross section tool
 - Thin-walled cross section assumption
 - Rigid cross section (Euler-Bernoulli)
 - Classic laminate theory
 - Written in C++
 - Python bindings with Swig
 - Will have analytic gradients
 - Within 10% compared to BECAS
- High fidelity cross section tool
 - Based on BECAS
 - BECAS uses an FE formulation
 - Solves the warping field
 - Gives fully populate matrix

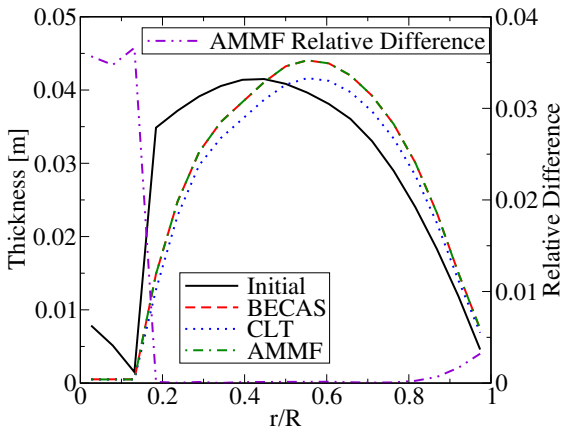
Operation	Calculation time [s]
Linear Beam Model	0.0035
LF cross section model	0.0074
BECAS	200.1866

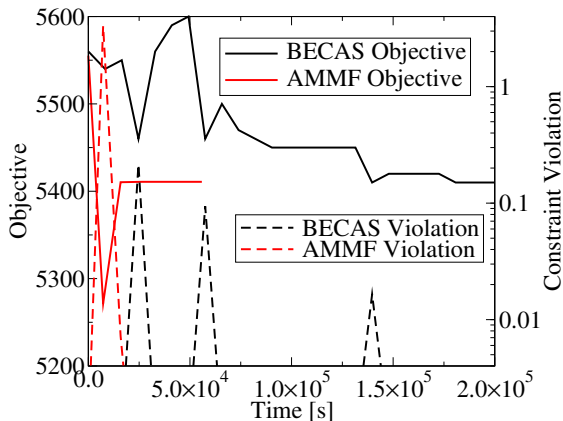
Table: Speed Comparison of Low Fidelity Tools

- Linear Beam Model
 - C++ code from my PhD
 - Analytic gradients wrt.
 - Positions
 - Orientation
 - Cross section properties
 - Applied forces
 - Solves equivalent forces for given deflection
- Speed comparison:
 - With python bindings
 - Calculation for whole blade
 - 19 elements
 - DTU 10MW

- Minimize DTU 10MW Blade Mass
- Varying spar cap thickness
- Subject to:
 - Tip deflection constraint
- Analysis based on the equivalent static problem (*i.e.* Frozen loads)
- Compared pure BECAS, pure CLT and AMMF
- Looked at various AMMF configurations:
 - Additive vs. Multiplicative corrections
 - Trust region size
 - Initial Lagrange multiplier (*i.e.* Penalty parameter)

- Low fidelity model is not conservative
 - Will produce infeasible solutions
- AMMF reproduced the BECAS solution
 - AMMF had better constraint resolution
- AMMF gives accurate corrections
- Additive vs multiplicative corrections:
 - Gives similar solutions
 - Similar performance

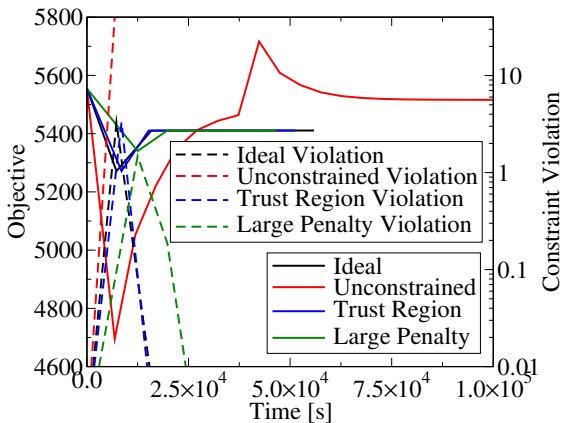




- AMMF converges 12 times faster
 - Just 2 major iterations
- AMMF had smoother convergence
 - Only 1 iteration with constraint violation
 - BECAS optimization ended due to maximum iterations
- Low fidelity models more suitable for optimization

AMMF guards against poor approximations

- Unconstrained has all protections disabled
 - Large violations
 - Fails to converge
- Trust region is most robust
 - Same progress as ideal configuration
- Large penalties work without trust region
 - No large violations
 - More searching



Closing Statements

- Higher fidelity in direct optimization is challenging but possible
 - Underlying tools may be non-smooth
 - Tools may need to be re-written or re-formulated (optimization proof)
 - Developed a totally new formulation for vortex methods based on FEM
 - Successfully obtained aero-elastic optimization results with vortex methods
- Higher fidelity through multi-fidelity design optimization is promising
 - Effective when low fidelity gives similar trends much faster
 - Achieved a 12 times speed up using multi-fidelity techniques
 - The AMMF algorithm is robust in handling errors
 - Ongoing case studies focusing on difficult problems

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Comments or Questions?